

# Subselect 0.9-99: Selecting variable subsets in multivariate linear models

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(\*) Supported by: FEDER / POCI 2010



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### A LINEAR HYPOTHESIS FRAMEWORK

$$X = A \Psi + U \quad H_0: C \Psi = 0$$

- SELECT COLUMNS OF X IN ORDER TO EXPLAIN H1

### PARTICULAR CASES:

CANONICAL CORRELATION ANALYSIS  $A = [1 | Y]$   $C = [0 | I]$

LINEAR DISCRIMINANT ANALYSIS

$$A = [1_g] \quad \Psi = [\mu_g] \quad C = \begin{bmatrix} 1 & -1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 1 & 0 & \dots & -1 \end{bmatrix}$$

MULTI-WAY MANOVA/MANCOVA EFFECTS

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**THE PROBLEM:** Finding a k-variable subset that is a good surrogate for a full p-variable data set

CONTEXT:

- Exploratory data analysis – Subselect 0.1-- 0.9  
(Cadima, Cerdeira, Duarte Silva and Minhoto -- useR! 2004)
- Multivariate Linear Models – Subselect 0.9-99

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$$\Omega = \mathcal{R}(A) \quad \omega = \mathcal{R}(A) \cap \mathcal{N}(C) \quad r = \dim(\Omega) - \dim(\omega)$$

$$ccr_i^2 = \text{Eigval}_i(T^{-1}H) \quad T = X'(I - P_\omega)X \quad H = X'(P_\Omega - P_\omega)X$$

Comparison Criteria: Multivariate Indices

$$ccr_1^2$$

$$( \max ccr_1^2 \Leftrightarrow \max \text{Roy } \lambda_1 )$$

$$\tau^2 = 1 - \left( \prod_{i=1}^r (1 - ccr_i^2) \right)^{1/r}$$

$$( \max \tau^2 \Leftrightarrow \min \text{Wilks } \Lambda )$$

$$\zeta^2 = 1 - \frac{r}{\sum_{i=1}^r (1 - ccr_i^2)^{-1}}$$

$$( \max \zeta^2 \Leftrightarrow \max \text{Lawley-Hotelling trace} )$$

$$\xi^2 = \frac{\sum_{i=1}^r ccr_i^2}{r}$$

$$( \max \xi^2 \Leftrightarrow \max \text{Bartlett-Pillai trace} )$$

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### The Subselect Package

Search routines for (combinatorial) criteria optimization

Exact Algorithm:

- leaps - based on Furnival and Wilson's leaps and bounds algorithm for linear regression
- viable with up to 30 - 35 original variables

Heuristics:

- anneal - simulated annealing
- genetic - genetic algorithm
- improve - restricted local improvement

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### Subselect in Multivariate Linear Models

Other arguments :

- Tuning parameters for heuristics
- Maximum time allowed for exact search
- Variables forcibly included or excluded in the selected subsets
- Number of solutions by subset dimensionality
- Numerical tolerance for detecting singular or non-symmetrical matrices

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### Subselect in Multivariate Linear Models

Principal arguments of search routines :

- mat - Total SSCP data matrix (T)
- H - Effect SSCP data matrix
- r - Expected rank of the H matrix
- criterion - "ccr12", "tau2", "xi2" or "zeta2"
- kmin, kmax - minimum and maximum subset dimensionalities sought

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### Subselect in Multivariate Linear Models

Auxiliary functions:

- lmHmat - creates H and mat matrices for linear regression/canonical correlation analysis
- ldaHmat - creates H and mat matrices for linear discriminant analysis
- glhHmat - creates H and mat matrices for an analysis based on a linear hypothesis specified by the user

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### Subselect in Multivariate Linear Models

#### Auxiliary functions :

- ccr12.coef, tau2.coef  
zeta2.coef, xi2.coef
- computes a comparison criterion for a subset supplied by the user
- trim.matrix
- deletes rows and columns of singular or ill-conditioned matrices
  - until all linear dependencies (perfect or almost perfect) are removed

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### Example: Hubbard Brook Forest soil data

Source: Morrison (1990)

#### Description:

58 pits were analyzed before (1983) and after (1986) harvesting (83-84) trees larger than a minimum diameter

Continuous variables: gr/m<sup>2</sup> of exchangeable cations

Al - Aluminum

K - Potassium

Ca - Calcium

Na - Sodium

Mg - Magnesium

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### Example: Hubbard Brook Forest soil data

Source: Morrison (1990)

#### Factors:

#### Factor levels:

- F - Forest Type
- 1 - Spruce- fir
  - 2 - High elevation hardwood
  - 3 - Low elevation hardwood
  - 0 - Uncut forest
- D - Logging Disturbance
- 1 - Cut, undisturbed by machinery
  - 2 - Cut, disturbed by machinery
- Year
- 1983 or 1986

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### Example: Hubbard Brook Forest soil data

Source: Morrison (1990)

#### Reading and preparing the data:

```
> library(subselect)
> HubForest <- read.table("Hubbard Brook.txt", header=T,
  col.names=c("Pit", "F", "D", "Al", "Ca", "Mg", "K", "Na", "Year"),
  colClasses=c("factor", "factor", "factor", "numeric",
    "numeric", "numeric", "numeric", "numeric", "factor"))
```

#### Analysis #1: Explaining the levels of calcium

```
> Hmat <- lmHmat(Ca ~ F*D + Al + Mg + K + Na, HubForest)
> colnames(Hmat$mat)
> leaps(Hmat$mat, H=Hmat$H, r=1, nsol=3)
```

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### Example: Hubbard Brook Forest soil data

Source: Morrison (1990)

#### Analysis #2: Looking for combinations of Forest type and Disturbance that best explain the nutrient levels

```
> Hmat <- lmHmat(cbind(Al,Ca,Mg,K,Na) ~ F*D,HubForest)
> colnames(Hmat$mat)
> leaps(Hmat$mat,H=Hmat$H,r=5,criterion="tau2",nsol=3)
```

#### Analysis #3: Finding which subsets of nutrients were most affected by the harvesting in 1983-84

```
> Hmat <- ldaHmat(Year ~ Al + Ca + Mg + K + Na , HubForest)
> leaps(Hmat$mat,H=Hmat$H,r=1,nsol=3)
```

#### References

Cadima J, Cerdeira JO and Minhoto M (2004). Computational Aspects of Algorithms for Variable Selection in the Context of Principal Components. *Computational Statistics and Data Analysis* **47**: 225-236.

Cadima J, Cerdeira JO, Duarte Silva AP and Minhoto M (2004). The Subselect Package; Selecting Variable Subsets in an Exploratory Data Analysis. *useR! 2004. 1rst Internatinal R User Conference. Vienna, Austria.*

Duarte Silva, A.P. (2001). Efficient Variable Screening for Multivariate Analysis. *Journal of Multivariate Analysis* **76**, 35-62.

Furnival, G.M. & Wilson, R.W. (1974). Regressions by Leaps and Bounds. *Technometrics* **16**: 499-511.

Morrison D.F. (1990). *Multivariate Statistical Methods*, 3rd ed., McGraw-Hill. New York, NY.

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### Example: Hubbard Brook Forest soil data

Source: Morrison (1990)

#### Analysis #4: Finding which subsets of nutrients are most affected by interactions between harvesting and logging disturbances, after controlling for the effect of forest type

```
> C <- matrix(0.,2,8)
> C[1,7] = C[2,8] = 1.
> Hmat <- glhHmat(cbind(Al,Ca,Mg,K,Na) ~ D*Year + F, C,
HubForest)
> leaps(Hmat$mat,H=Hmat$H,r=2, criterion="tau2",
nsol=3,tolsym=1E-10)
```